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EXAMINER	
MORGAN, ROBERT W	
ART UNIT	**PAPER NUMBER**
3626	

DATE MAILED: 04/07/2006

Please find below and/or attached an Office communication concerning this application or proceeding.

Office Action Summary	Application No.	Applicant(s)	
	10/076,961	SURESH ET AL.	
	Examiner	Art Unit	
	Robert W. Morgan	3626	

-- The MAILING DATE of this communication appears on the cover sheet with the correspondence address --

Period for Reply

A SHORTENED STATUTORY PERIOD FOR REPLY IS SET TO EXPIRE 3 MONTH(S) OR THIRTY (30) DAYS, WHICHEVER IS LONGER, FROM THE MAILING DATE OF THIS COMMUNICATION.

- Extensions of time may be available under the provisions of 37 CFR 1.136(a). In no event, however, may a reply be timely filed after SIX (6) MONTHS from the mailing date of this communication.
- If NO period for reply is specified above, the maximum statutory period will apply and will expire SIX (6) MONTHS from the mailing date of this communication.
- Failure to reply within the set or extended period for reply will, by statute, cause the application to become ABANDONED (35 U.S.C. § 133). Any reply received by the Office later than three months after the mailing date of this communication, even if timely filed, may reduce any earned patent term adjustment. See 37 CFR 1.704(b).

Status

1)☒ Responsive to communication(s) filed on *10 January 2006*.

2a)☐ This action is **FINAL**. 2b)☒ This action is non-final.

3)☐ Since this application is in condition for allowance except for formal matters, prosecution as to the merits is closed in accordance with the practice under *Ex parte Quayle*, 1935 C.D. 11, 453 O.G. 213.

Disposition of Claims

4)☒ Claim(s) *1-5 and 7-19* is/are pending in the application.

4a) Of the above claim(s) _____ is/are withdrawn from consideration.

5)☐ Claim(s) _____ is/are allowed.

6)☒ Claim(s) *1-5 and 7-19* is/are rejected.

7)☐ Claim(s) _____ is/are objected to.

8)☐ Claim(s) _____ are subject to restriction and/or election requirement.

Application Papers

9)☐ The specification is objected to by the Examiner.

10)☐ The drawing(s) filed on _____ is/are: a)☐ accepted or b)☐ objected to by the Examiner.

Applicant may not request that any objection to the drawing(s) be held in abeyance. See 37 CFR 1.85(a).

Replacement drawing sheet(s) including the correction is required if the drawing(s) is objected to. See 37 CFR 1.121(d).

11)☐ The oath or declaration is objected to by the Examiner. Note the attached Office Action or form PTO-152.

Priority under 35 U.S.C. § 119

12)☐ Acknowledgment is made of a claim for foreign priority under 35 U.S.C. § 119(a)-(d) or (f).

a)☐ All b)☐ Some * c)☐ None of:

1.☐ Certified copies of the priority documents have been received.

2.☐ Certified copies of the priority documents have been received in Application No. _____.

3.☐ Copies of the certified copies of the priority documents have been received in this National Stage application from the International Bureau (PCT Rule 17.2(a)).

* See the attached detailed Office action for a list of the certified copies not received.

Attachment(s)

1) ☐ Notice of References Cited (PTO-892)
2) ☐ Notice of Draftsperson's Patent Drawing Review (PTO-948)
3) ☐ Information Disclosure Statement(s) (PTO-1449 or PTO/SB/08) Paper No(s)/Mail Date _____.
4) ☐ Interview Summary (PTO-413) Paper No(s)/Mail Date. _____ .
5) ☐ Notice of Informal Patent Application (PTO-152)
6) ☐ Other: _____.

DETAILED ACTION

Continued Examination Under 37 CFR 1.114

1. A request for continued examination under 37 CFR 1.114, including the fee set forth in 37 CFR 1.17(e), was filed in this application after final rejection. Since this application is eligible for continued examination under 37 CFR 1.114, and the fee set forth in 37 CFR 1.17(e) has been timely paid, the finality of the previous Office action has been withdrawn pursuant to 37 CFR 1.114. Applicant's submission filed on 1/10/06 has been entered.

Notice to Applicant

2. In amendment filed on 1/10/06 the following has occurred: Claims 1-2, 8-9 and 15 have been amended. Now claims 1-5 and 7-19 are presented for examination.

Claim Rejections - 35 USC § 103

3. The following is a quotation of 35 U.S.C. 103(a) which forms the basis for all obviousness rejections set forth in this Office action:

> (a) A patent may not be obtained though the invention is not identically disclosed or described as set forth in section 102 of this title, if the differences between the subject matter sought to be patented and the prior art are such that the subject matter as a whole would have been obvious at the time the invention was made to a person having ordinary skill in the art to which said subject matter pertains. Patentability shall not be negatived by the manner in which the invention was made.

3. Claims 1-2, 7, 15 and 19 are rejected under 35 U.S.C. 103(a) as being unpatentable over U.S. Patent No. 5,253,164 to Holloway et al. and U.S. Patent No. 6,253,186 to Pendleton, Jr. et al. in view of "Maximum likelihood continuity mapping for fraud detection" to Hogden.

As per claim 1, Holloway et al. teaches a method and system for detecting fraudulent medical claims including an expert computer system using a set of decision-making rules coupled to a knowledge base of facts and observations to assist the medical claims process (see: column 3, lines 30-32 and 51-54).

Holloway et al. fails to teach:

--the claimed determining a sequence of healthcare states, wherein a healthcare states is any of, but not limited to a provider and a facility, for a client from healthcare reimbursement claims associated with the client and storing said sequence in any of:

a data structure in a system database; and

in working memory, and

--the claimed processing healthcare reimbursement claims for a population of clients and healthcare providers for a selected time interval to identify a total set of potential healthcare states in a collection of healthcare data;

--the claimed calculating a probability of the sequence of healthcare states based on previously calculated probabilities of individual transition between healthcare states as contained in a model derived from the collection of health data, and based on aggregated sequence probability information from previously processed individual sequence probabilities; and

--the claimed identifying the sequence as potentially fraudulent as a function of the probability of the sequence wherein said probability of sequence is distinct.

Pendleton, Jr. teaches a method and apparatus for detecting potentially fraudulent suppliers or providers of goods or services including the steps of: a) collecting data on a plurality of suppliers and providers, including data relating to claims submitted for payment by the suppliers and providers; b) processing the data to produce a fraud indicator for at least one of the suppliers and providers; and c) determining, using the fraud indicator, whether the selected supplier or provider is a potentially fraudulent supplier or provider (see: column 1, lines 49-60). Pendleton, Jr. further teaches the use of a composite fraud indicator that is computed by

averaging a plurality of fraud indicators for the selected provider or supplier (see: column 2, lines 23-25). Pendleton, Jr. also teaches that other approaches include computing a weighted average of the individual fraud indicators, of selecting a subset of the indicators for use in computing the composite fraud indicator. After the composite fraud indicator is computed, it is compared to a threshold number, which is based upon prior experience (block 70) (see: column 7, lines 32-37). Furthermore, any supplier or provider that exceeds the fraud indicator threshold value is stored in the NN data base file for tracking purposes (see: column 7, lines 41-47). Moreover, Pendleton, Jr. teaches a process by which a neural network (reads "working memory") analyzes the claim line information in the claim file (48, Fig. 5) to produce a number or score for each claim line which is viewed as a fraud index or indicator (see: column 7, lines 5-9). The Examiner considers the number or score for each claim line mentioned above as the information necessary to compute a transition sequence used in calculating a transition metric for transition between states (reads on "previously calculated probabilities of individual transition between healthcare states"). Additionally, Pendleton, Jr. et al. teaches that historical data is extracted for a selected supplier or provider with reference to the claim analysis network over a period of time (e.g. 6 months) (reads on "processing healthcare reimbursement claims for a population of clients and healthcare providers for a selected time interval") (see: column 12, lines 12-25).

One of ordinary skill in the art at the time the invention was made would have found it obvious to include the fraud indicator and threshold values for detecting potentially fraudulent suppliers or providers of goods or services as taught by Pendleton, Jr. et al. with the method and system for detecting fraudulent medical claims as taught by Holloway et al. with the motivation of providing an automated system for processing a large number of claims submitting to payor to

identify patterns in the claim data which may be indicative of a fraudulent provider or supplier (see: Pendleton et al.: column 1, lines 27-30).

Holloway et al. and Pendleton, Jr. et al. fails to teach the claimed calculating a probability of the sequence of healthcare states based on a model derived from a collection of health data, and based on aggregated sequence probability information from previously processed individual sequence probabilities.

Hogden teaches an analysis technique called maximum likelihood continuity mapping (MALCOM) for detecting fraud in medical insurance claims (see: abstract). Hogden further teaches a time-series analysis technique used to estimate the likelihood of a data sequences using training data composed of sequences of symbols such as medical procedure codes to create a model of sequence generation (see: page 2, paragraph 5). In addition, Hogden also teaches estimating probability of sequence symbols using a continuity map (see: page 4, paragraph 2). In addition,

Therefore, it would have been obvious to a person of ordinary skill in art at the time the invention was made include the time-series analysis technique as taught by Hogden with the system as taught by Holloway et al. and Pendleton, Jr. et al. with the motivation of describing how the method of time-series analysis can be formed and used for anomaly detection (see: page 10, paragraph 3).

As per claim 2, Holloway et al. teaches that a user entering claim information into the computer system (2, Fig. 1) which is sent to a knowledge base interpreter (5, Fig. 1) for assessment of the claim and a recommendation is returned to the user as to whether the claim is

proper or improper (see: column 4, lines 51-64). The Examiner considers the steps involved with processing, analyzing and verifying the claim as a sequence of healthcare states.

However, Holloway et al. fails to teach for each healthcare state transition determining a probability of the healthcare state transition as a function of the frequency of the healthcare state transition in the reimbursement claims.

Pendleton Jr. et al. teaches the use of a composite fraud indicator that is computed by averaging a plurality of fraud indicators for the selected provider or supplier (see: column 2, lines 23-25). Pendleton, Jr. also teaches that other approaches include computing a weighted average (reads on "determining probability and function of the frequency") of the individual fraud indicators, of selecting a subset of the indicators for use in computing the composite fraud indicator. After the composite fraud indicator is computed, it is compared to a threshold number, which is based upon prior experience (block 70) (see: column 7, lines 32-37). Moreover, Pendleton, Jr. teaches a process by which a neural network analyzes the claim line information in the claim file (48, Fig. 5) to produce a number or score for each claim line which is viewed as a fraud index or indicator (see: column 7, lines 5-9). The Examiner considers the number or score for each claim line mentioned above as the information necessary to compute a transition sequence used in calculating a transition metric for transition between states (reads on "transition between healthcare states").

The obviousness of combining the teachings of Pendleton Jr. et al. with the system as taught by Holloway et al. are discussed in the rejection of claim 1, and incorporated herein.

As per claim 7, Holloway teaches a method and system for detecting fraudulent medical claims including an expert computer system using a set of decision-making rules coupled to a

knowledge base of facts and observations to assist the medical claims process (see: column 3, lines 30-32 and 51-54).

Holloway fails to explicitly teach the claimed each client in a population of clients, determining a transition probability for each sequence of healthcare states experienced by the client.

Pendleton Jr. et al. teach a composite fraud indicator that is computed by averaging a plurality of fraud indicators for the selected provider or supplier (see: column 2, lines 23-25). Additionally, Pendleton, Jr. et al. teaches that other approaches include computing a weighted average of the individual fraud indicators, of selecting a subset of the indicators for use in computing the composite fraud indicator. After the composite fraud indicator is computed, it is compared to a threshold number, which is based upon prior experience (block 70) (see: Pendleton Jr. et al.: column 7, lines 32-37). Since Pendleton Jr. et al. teach a mathematical method for computing the fraud indicator using averages, weighted averages and threshold values as noted above and also teaches the use of a claim file (26, Fig. 4) that includes healthcare states such as Health Care Procedure Code System (HCPCS) code, other codes, dates, units, pricing information, total dollar amount requested, or other information (see: Pendleton Jr. et al.: column 6, lines 10-20).

The obviousness of combining the teachings of Pendleton Jr. et al. with the system as taught by Holloway et al. are discussed in the rejection of claim 1, and incorporated herein.

Pendleton Jr. et al. and Holloway et al. fail to teach the claims transition probability for each sequence of healthcare states.

Hogden teaches an analysis technique called maximum likelihood continuity mapping (MALCOM) for detecting fraud in medical insurance claims (see: abstract). Hogden further teaches a time-series analysis technique used to estimate the likelihood of a data sequences using training data composed of sequences of symbols such as medical procedure codes to create a model of sequence generation (see: page 2, paragraph 5). In addition, Hogden teaches that after training the model can be used to determine the probability of a sequence of symbols.

The obviousness of combining the teachings of Hogden with the system as taught by Pendleton Jr. et al. and Holloway et al. are discussed in the rejection of claim 1, and incorporated herein.

As per claim 15, Holloway et al. teaches a method and system for detecting fraudulent medical claims including an expert computer system using a set of decision-making rules coupled to a knowledge base of facts and observations to assist the medical claims process (see: column 3, lines 30-32 and 51-54). Holloway et al. further teaches that each claim (1, Fig. 1) is entered into a computer system (2, Fig. 1) containing sufficient data processing and memory and suitable commercially available database management software programs with facts including one or more medical procedures for which payment is sought, other data such age of the patient, claim number, date(s) of treatment(s) and procedure(s), the name of physician, etc. (see: column 4, lines 23-40).

Holloway et al. fails to teach a system for creating models of healthcare claims, comprising:

--the claimed healthcare reimbursement claims are processed for a population of clients and healthcare providers for a selected time interval to identify a total set of potential healthcare states in a collection of healthcare data;

--the claimed data processing module that processes a set of the claims into date-ordered, entity specific sequences of states, wherein a state comprises any of, but not limited to:

--the claimed facilities providing procedures to clients, services codes for healthcare procedures, healthcare providers, provider-days, and provider-service codes;

--the claimed transition processing module that determines, from the date ordered entity specific sequences; and

--the claimed entity profiling module that generates profiles for at least one entity, a transition metric for one or more sequences of states related to the entity.

Pendleton Jr. et al. teaches a claim file (26, Fig. 4) that includes healthcare states such as Health Care Procedure Code System (HCPCS) code, other codes, dates, units, pricing information, total dollar amount requested, or other information (see: column 6, lines 10-20). Pendleton Jr. et al. further teaches that the claim file (26, Fig. 4) is sorted in a sort operation (46, Fig. 5) and the data is encoded in a claim data file (40, Fig. 4) (see: column 6, lines 39-53). The Examiner considers that since the claim file contains information such as claim dates and is sorted by a sort operation, this suggests that the claims are date ordered. Pendleton Jr. et al. also teaches a composite fraud indicator that is computed by averaging a plurality of fraud indicators for the selected provider or supplier (see: column 2, lines 23-25). In addition, Pendleton, Jr. et al. teaches that other approaches include computing a weighted average of the individual fraud indicators, of selecting a subset of the indicators for use in computing the composite fraud

indicator. After the composite fraud indicator is computed, it is compared to a threshold number, which is based upon prior experience (block 70) (see: column 7, lines 32-37). Furthermore, Pendleton Jr. et al. teaches that once a supplier or provider using the fraud indicator exceeds the threshold number the results for the subject supplier or provider are written to neural network (NN) data base file (72, Fig. 7) (see: column 7, lines 41-45). Moreover, Pendleton, Jr. teaches a process by which a neural network analyzes the claim line information in the claim file (48, Fig. 5) to produce a number or score for each claim line which is viewed as a fraud index or indicator (see: column 7, lines 5-9). The Examiner considers the number or score for each claim line mentioned above as the information necessary to compute a transition sequence used in calculating a transition metric for transition between states (reads on "transition between healthcare states"). Additionally, Pendleton, Jr. et al. teaches that historical data is extracted for a selected supplier or provider with reference to the claim analysis network over a period of time (e.g. 6 months) (reads on "healthcare reimbursement claims are processed for a population of clients and healthcare providers for a selected time interval") (see: column 12, lines 12-25).

The obviousness of combining the teachings of Pendleton Jr. et al. with the system as taught by Holloway et al. are discussed in the rejection of claim 1, and incorporated herein.

Pendleton Jr. et al. and Holloway et al. fail to teach the claimed transition metric for each transition between states, wherein said transition metric for each transition between states is based of frequency counts of a transition form a first state to a next state.

Hogden teaches an analysis technique called maximum likelihood continuity mapping (MALCOM) for detecting fraud in medical insurance claims (see: abstract). Hogden further teaches a time-series analysis technique used to estimate the likelihood of a data sequences using

training data composed of sequences of symbols such as medical procedure codes to create a model of sequence generation (see: page 2, paragraph 5). In addition, Hogden teaches that after training the model can be used to determine the probability of a sequence of symbols.

The obviousness of combining the teachings of Hogden with the system as taught by Pendleton Jr. et al. and Holloway et al. are discussed in the rejection of claim 1, and incorporated herein.

As per claim 19, Holloway et al. teaches wherein an entity is one for the group consisting of: a client; a healthcare provider; a provider/client; or a procedure. This feature is met by each claim (1, Fig. 1) which is entered into a computer system (2, Fig. 1) containing sufficient data processing and memory and suitable commercially available database management software programs with facts including one or more medical procedures for which payment is sought, other data such age of the patient, claim number, date(s) of treatment(s) and procedure(s), the name of physician, etc. (see: column 4, lines 23-40).

5. Claims 3-5, 8-14 and 16-18 are rejected under 35 U.S.C. 103(a) as being unpatentable over U.S. Patent No. 6,253,186 to Pendleton, Jr. et al. in view of "Maximum likelihood continuity mapping for fraud detection" to Hogden.

As per claim 3, Pendleton Jr. et al. teaches a method for identifying potentially fraudulent or abusive treatment practices by healthcare providers, comprising:

--the claimed processing healthcare reimbursement claims for a population of clients and healthcare providers for a selected time interval for treatments provided by the providers, to identify a total set of potential healthcare states in collection of healthcare data and to determine transition probabilities for sequences of healthcare states for the treatments is met by the

composite fraud indicator that is computed by averaging a plurality of fraud indicators for the selected provider or supplier (see: column 2, lines 23-25). In addition, Pendleton, Jr. et al. teaches that other approaches include computing a weighted average of the individual fraud indicators, of selecting a subset of the indicators for use in computing the composite fraud indicator. After the composite fraud indicator is computed, it is compared to a threshold number, which is based upon prior experience (block 70) (see: column 7, lines 32-37). Moreover, Pendleton, Jr. teaches a process by which a neural network analyzes the claim line information in the claim file (48, Fig. 5) to produce a number or score for each claim line which is viewed as a fraud index or indicator (see: column 7, lines 5-9). The Examiner considers the number or score for each claim line mentioned above as the information necessary to compute a transition sequence used in calculating a transition metric for transition between states. Additionally, Pendleton, Jr. et al. teaches that historical data is extracted for a selected supplier or provider with reference to the claim analysis network over a period of time (e.g. 6 months) (see: column 12, lines 12-25);

--the claimed for each provider, determining an aggregated transition probability for all sequences of healthcare states for treatments provided by the provider is met by the statistical information which access provider stat file (90, Fig. 8) and compiled in a statistical system update (see: column 8, lines 14-17); and

--the claimed identifying as potentially fraudulent at least one provider having aggregated transition probability that is statistically different from the aggregate transition probabilities of similar providers is met by the process accumulating the data involving simply adding the fraud

indicators produce for each claim line to produce a total for a particular supplier or provider (see: column 7, lines 10-14).

Pendleton Jr. et al. teaches a mathematical method for computing the fraud indicator using averages, weighted averages and threshold values as noted above. In addition, Pendleton Jr. et al. teaches use of a claim file (26, Fig. 4) that includes healthcare states such as Health Care Procedure Code System (HCPCS) code, other codes, dates, units, pricing information, total dollar amount requested, or other information (see: column 6, lines 10-20). The above-mentioned healthcare states are utilized to compute the fraud indicator and threshold values and subsequently the transition probabilities sequences from the healthcare states.

Pendleton Jr. et al. fails to explicitly teach:

--the claimed transition probabilities sequences of healthcare states; and

--the claimed transition probabilities for sequences are determined based on previously calculated probabilities of individual ones of the healthcare states as contained in a model derived from the collection of healthcare data.

Hogden teaches an analysis technique called maximum likelihood continuity mapping (MALCOM) for detecting fraud in medical insurance claims (see: abstract). Hogden further teaches a time-series analysis technique used to estimate the likelihood of a data sequences using training data composed of sequences of symbols such as medical procedure codes to create a model of sequence generation (see: page 2, paragraph 5). In addition, Hogden also teaches estimating probability of sequence symbols using a continuity map (see: page 4, paragraph 2).

Therefore, it would have been obvious to a person of ordinary skill in art at the time the invention was made include the time-series analysis technique as taught by Hogden with the

system as taught by Holloway et al. and Pendleton, Jr. et al. with the motivation of describing how the method of time-series analysis can be formed and used for anomaly detection (see: page 10, paragraph 3).

As per claim 4, Pendleton Jr. et al. teaches determining an aggregated transition probability for all sequences of healthcare states for treatment provided by the provider comprises:

--the claimed for each client treated by a provider, determining a transition probability for each sequence of healthcare states including at least one treatment provided by the provider the client is met by the claim file (26, Fig. 4) that includes healthcare states such as Health Care Procedure Code System (HCPCS) code, other codes, dates, units, pricing information, total dollar amount requested, or other information (see: column 6, lines 10-20); and

--the claimed determining the aggregated transition probability for the provider as a function of the transition probabilities determined for each sequence of each client.

Pendleton Jr. et al. teaches a mathematical method for computing the fraud indicator using averages, weighted averages and threshold values as noted above. In addition, Pendleton Jr. et al. teaches use of a claim file (26, Fig. 4) that includes healthcare states such as Health Care Procedure Code System (HCPCS) code, other codes, dates, units, pricing information, total dollar amount requested, or other information (see: column 6, lines 10-20).

Pendleton Jr. et al. fails to explicitly transition probability for each and all sequence of healthcare states.

Hogden teaches an analysis technique called maximum likelihood continuity mapping (MALCOM) for detecting fraud in medical insurance claims (see: abstract). Hogden further

teaches a time-series analysis technique used to estimate the likelihood of a data sequences using training data composed of sequences of symbols such as medical procedure codes to create a model of sequence generation (see: page 2, paragraph 5). In addition, Hogden also teaches estimating probability of sequence symbols using a continuity map (see: page 4, paragraph 2).

The obviousness of combining the teachings of Hogden within the teachings of Pendleton Jr. et al. are discussed in rejection of claim 3, and incorporated herein.

As per claim 5, Pendleton Jr. et al. fails to explicitly teach:

--the claimed for each pair of states, there is a transition probability for a transition between the states; and

--the claimed transition probability for a sequence of states is the geometric mean of the transition probabilities between each state and the next state in the sequence.

Hogden teaches an analysis technique called maximum likelihood continuity mapping (MALCOM) for detecting fraud in medical insurance claims (see: abstract). Hogden further teaches a time-series analysis technique used to estimate the likelihood of a data sequences using training data composed of sequences of symbols such as medical procedure codes to create a model of sequence generation (see: page 2, paragraph 5). In addition, Hogden also teaches estimating probability of sequence symbols using a continuity map (see: page 4, paragraph 2). Additionally, Hogden teaches the use geometric mean to calculate the probability of symbol sequences using the continuity map (see: page 5, paragraph 2-8 and equation 1 and 2).

The obviousness of combining the teachings of Hogden within the teachings of Pendleton Jr. et al. are discussed in rejection of claim 3, and incorporated herein.

As per claim 8, Pendleton Jr. et al. teaches a method for creating a model of healthcare states, comprising:

--the claimed processing healthcare reimbursement claims for a population of clients and healthcare providers for a selected time interval to identify a total set of potential healthcare states in a collection of healthcare data, each reimbursement claim related to a client and healthcare treatment is met by a process by which a neural network analyzes the claim line information in the claim file (48, Fig. 5) to produce a number or score for each claim line which is viewed as a fraud index or indicator (see: column 7, lines 5-9). The Examiner considers the number or score for each claim line mentioned above as the information necessary to compute a transition sequence used in calculating a transition metric for transition between states. Additionally, Pendleton, Jr. et al. teaches that historical data is extracted for a selected supplier or provider with reference to the claim analysis network over a period of time (e.g. 6 months) (see: column 12, lines 12-25);

for each client:

--the claimed extracting from the claims related to the client a plurality of treatments is met by the extraction of claim data in the first step of data collection function (see: column 5, lines 21-35);

--the claimed determining at least one sequence of healthcare states from the treatments, each state associated with a provider is met by the claim lines and the term "lines" represents request for money to be paid in return for each product or service (see: column 5, lines 36-40);

--the claimed for each pair of states in each sequence, updating a frequency count of a transition from a first state to a next state is met by the process of accumulating data involves

adding fraud indicators produced for each claim line to produce a total for a particular supplier or provider (see: column 7, lines 9-13);

--the claimed for each state, determining a total count of transitions from the state to all other states based on the frequency counts is met by the process of accumulating data involves adding fraud indicators produced for each claim line to produce a total for a particular supplier or provider (see: column 7, lines 9-13); and

--the claimed creating a look-up in said model is met by the creation of lookup tables stored for use by the system (see: column 11, lines 18-57 and Fig. 4, 15 and 16).

Pendleton Jr. et al. teaches a composite fraud indicator that is computed by averaging a plurality of fraud indicators for the selected provider or supplier (see: column 2, lines 23-25). In addition, Pendleton, Jr. et al. teaches that other approaches include computing a weighted average of the individual fraud indicators, of selecting a subset of the indicators for use in computing the composite fraud indicator. After the composite fraud indicator is computed, it is compared to a threshold number, which is based upon prior experience (block 70) (see: column 7, lines 32-37). Since Pendleton Jr. et al. teaches a mathematical method for computing the fraud indicator using averages, weighted averages and threshold values as noted above and also teaches the use of a claim file (26, Fig. 4) that includes healthcare states such as Health Care Procedure Code System (HCPCS) code, other codes, dates, units, pricing information, total dollar amount requested, or other information (see: column 6, lines 10-20).

Pendleton Jr. et al. fails to explicitly teach:

--the claimed each sequence comprises one or more transition between states;

--the claimed transition probabilities for each state transition; and

--the claimed for each state transition from a first state to a next state, determining a transition probability for the state transition as the ratio of the frequency count from the first state to the next state, to total count of transition for the first state to all other states.

Hogden teaches an analysis technique called maximum likelihood continuity mapping (MALCOM) for detecting fraud in medical insurance claims (see: abstract). Hogden further teaches a time-series analysis technique used to estimate the likelihood of a data sequences using training data composed of sequences of symbols such as medical procedure codes to create a model of sequence generation (see: page 2, paragraph 5). In addition, Hogden teaches that after training the model can be used to determine the probability of a sequence of symbols (see: page 2, paragraph 5). Furthermore, Hogden teaches estimating probability of sequence symbols using a continuity map (see: page 4, paragraph 2).

The obviousness of combining the teachings of Hogden within the teachings of Pendleton Jr. et al. are discussed in rejection of claim 3, and incorporated herein.

As per claim 9, Pendleton Jr. et al. teaches a method of profiling healthcare entities, the method comprising:

--the claimed processing healthcare reimbursement claims for a population of clients and healthcare providers for a selected time interval to identify a total set of potential healthcare states in a collection of healthcare data is met by a process by which a neural network analyzes the claim line information in the claim file (48, Fig. 5) to produce a number or score for each claim line which is viewed as a fraud index or indicator (see: column 7, lines 5-9). The Examiner considers the number or score for each claim line mentioned above as the information necessary to compute a transition sequence used in calculating a transition metric for transition between

states. Additionally, Pendleton, Jr. et al. teaches that historical data is extracted for a selected supplier or provider with reference to the claim analysis network over a period of time (e.g. 6 months) (see: column 12, lines 12-25);

--the claimed determining at least one sequence of healthcare states for an from healthcare reimbursement claims associated with the entity is met by the process of updating provider stat file (92, Fig. 14) by applying the statistical fraud analysis models (212, Fig. 14) to provider history data from the application data base (202, Fig. 14) to examine historical provider characteristics which are highly indicative or suspect behavior (see: column , lines 36-46).

Pendleton Jr. et al. teaches a composite fraud indicator that is computed by averaging a plurality of fraud indicators for the selected provider or supplier (see: column 2, lines 23-25). In addition, Pendleton, Jr. et al. teaches that other approaches include computing a weighted average of the individual fraud indicators, of selecting a subset of the indicators for use in computing the composite fraud indicator. After the composite fraud indicator is computed, it is compared to a threshold number, which is based upon prior experience (block 70) (see: column 7, lines 32-37). Since Pendleton Jr. et al. teaches a mathematical method for computing the fraud indicator using averages, weighted averages and threshold values as noted above and also teaches the use of a claim file (26, Fig. 4) that includes healthcare states such as Health Care Procedure Code System (HCPCS) code, other codes, dates, units, pricing information, total dollar amount requested, or other information (see: column 6, lines 10-20).

Pendleton Jr. et al. fails to explicitly teach:

--the claimed wherein a sequence of healthcare states represents client experiences in one or more episodes of care;

--the claimed determining a probability of each sequence based on previously determined probabilities of transitions between healthcare states, wherein a previously determined transition probability of a individual healthcare state is determined using look-up table of Claim 8; and

--the claimed assigning to a profile of the entity a transition metric based on the probability of each sequence.

Hogden teaches an analysis technique called maximum likelihood continuity mapping (MALCOM) for detecting fraud in medical insurance claims (see: abstract). Hogden further teaches a time-series analysis technique used to estimate the likelihood of a data sequences using training data composed of sequences of symbols such as medical procedure codes to create a model of sequence generation (see: page 2, paragraph 5). In addition, Hogden teaches that after training the model can be used to determine the probability of a sequence of symbols (see: page 2, paragraph 5). Furthermore, Hogden teaches estimating probability of sequence symbols using a continuity map (see: page 4, paragraph 2).

The obviousness of combining the teachings of Hogden within the teachings of Pendleton Jr. et al. are discussed in rejection of claim 3, and incorporated herein.

As per claims 10-14, Pendleton Jr. et al. teaches the healthcare states are facilities providing procedures to clients, service codes for healthcare procedures, healthcare providers, provider-days and provider-service codes. These features are met by the claim file (26, Fig. 4) that includes healthcare states such as Health Care Procedure Code System (HCPCS) code, other codes, dates, units, pricing information, total dollar amount requested, or other information (see: column 6, lines 10-20).

As per claim 16, Pendleton Jr. et al. fails to explicitly teach the claimed an analytical module that receives the profiles and identifies entities that are potentially fraudulent or abusive based at least in part upon the transition metrics contained in the profiles.

However, Pendleton Jr. et al. teaches a composite fraud indicator that is computed by averaging a plurality of fraud indicators for the selected provider or supplier (see: column 2, lines 23-25). In addition, Pendleton, Jr. et al. teaches that other approaches include computing a weighted average of the individual fraud indicators, of selecting a subset of the indicators for use in computing the composite fraud indicator. After the composite fraud indicator is computed, it is compared to a threshold number, which is based upon prior experience (block 70) (see: column 7, lines 32-37). Furthermore, Pendleton Jr. et al. teaches that once a supplier or provider, using the fraud indicator exceeds the threshold number the results for the subject supplier or provider are written to neural network (NN) data base file (72, Fig. 7) (see: column 7, lines 41-45). The Examiner considers the suppliers or providers written to the NN database file to be profiles and identities of supplier or provider that are part of potentially fraudulent or abusive practices. Since Pendleton Jr. et al. teaches a mathematical method for computing the fraud indicator using averages, weighted averages and threshold values as noted above. It would have obvious to use mathematical methods along with an analytical module that receives the profiles and identifies entities that are potentially fraudulent or abusive based at least in part upon the transition metrics contained in the profiles.

The obviousness of using a mathematical or statistical method along with an analytical module that receives the profiles and identifies entities that are potentially fraudulent or abusive

based at least in part upon the transition metrics contained in the profiles within the teachings of Pendleton Jr. et al. are discussed in the rejection of claim 3, and incorporated herein.

As per claims 17-18, Pendleton Jr. et al. teaches the claimed analytical module includes a predictive model and rules based model. This limitation is met by the providers that undergo analysis using statistical screening models and a fuzzy logic analysis of model results to produce a fraud prediction model (see: column 8, lines 36-58). Pendleton Jr. et al. further teaches the use of an expert system interface engine (block 160, Fig. 12) that analyses each record of a particular provider using expert system rules (162, Fig. 12) (see: column 9, lines 35-45).

Response to Arguments

6. Applicant's arguments filed 1/10/06 have been fully considered but they are not persuasive. Applicant's arguments will be addressed hereinbelow in the order in which they appear in the response 1/10/06.

(A) In the remarks, Applicants argue in substance that, (1) the Examiner has still failed to establish a *prima facie* case of obviousness and the findings are guided by impermissible hindsight; (2) the Examiner response did not constitute a rebuttal of Applicant's argument in the previous Office Action; (3) the Examiner's collection of cited legal precedent such as the *per se* rules of obviousness are not supported by the Examiner's position and an explanation of why those legal conclusions should apply here is not provided; and (4) Hogden explicitly teach away from the invention that recites "calculating a probability of the sequence of health care sates based on previously calculated probabilities of individual transitions between healthcare states as contained in a model derived from the collection of healthcare data, and based on aggregated

sequence probability information from previously processed individual sequence probabilities...".

(B) In response to Applicant's argument that, (1) the Examiner has still failed to establish a *prima facie* case of obviousness and the findings are guided by impermissible hindsight; (2) the Examiner response did not constitute a rebuttal of Applicant's argument in the previous Office Action; and (3) the Examiner's collection of cited legal precedent such as the *per se* rules of obviousness are not supported by the Examiner's position and an explanation of why those legal conclusions should apply here is not provided. The Examiner respectfully submits that it must be recognized that any judgment on obviousness is in a sense necessarily a reconstruction based upon hindsight reasoning. But so long as it takes into account only knowledge which was within the level of ordinary skill at the time the claimed invention was made, and does not include knowledge gleaned only from the Applicant's disclosure, such a reconstruction is proper. See *In re McLaughlin*, 443 F.2d 1392, 170 USPQ 209 (CCPA 1971). Moreover, Applicant seems to be arguing case law rather than the manner in which the prior art of Holloway et al., Pendleton Jr. et al., Hogden and Seare et al. have been applied to Applicant's invention. In addition, the more recent 1998 case of *Monarch Knitting Machinery Corp v. Sulzer Morat GmBH*, 139 F.3d 877 (Fed. Cir 1998), does not vacant or nullified the previous court case of *In re McLaughlin*, 443 F.2d 1392, 170 USPQ 209 (CCPA 1971) regarding hindsight. Furthermore, the facts of the *Monarch Knitting Machinery Corp v. Sulzer Morat GmBH* are not applicable to the subject matter of Applicant's claimed invention.

(C) In response to Applicant's argument that, (4) Hogden explicitly teach away from the invention that recites "calculating a probability of the sequence of health care sates based on

previously calculated probabilities of individual transitions between healthcare states as contained in a model derived from the collection of healthcare data, and based on aggregated sequence probability information from previously processed individual sequence probabilities...". The Examiner respectfully submits that this is not evidence that the applied references teach away from applicant invention. In addition, it is the Pendleton, Jr. that is relied on for teachings a method and apparatus for detecting potentially fraudulent suppliers or providers of goods or services including the steps of: a) collecting data on a plurality of suppliers and providers, including data relating to claims submitted for payment by the suppliers and providers; b) processing the data to produce a fraud indicator for at least one of the suppliers and providers; and c) determining, using the fraud indicator, whether the selected supplier or provider is a potentially fraudulent supplier or provider (see: column 1, lines 49-60). Pendleton, Jr. also teaches a process by which a neural network analyzes the claim line information in the claim file (48, Fig. 5) to produce a number or score for each claim line which is viewed as a fraud index or indicator (see: column 7, lines 5-9). The clearly shows that the number or score for each claim line mentioned above is used as information necessary to compute a transition sequence used in calculating a transition metric for transition between states. Furthermore, it is respectfully submitted that if Applicant's were correct in his assertion which Examiner does not admit, it has been held that prior art reference must be considered in its entirety, i.e., as a whole, including portions that would lead away from the claimed invention. *W.L. Gore & Associates, Inc. v. Garlock, Inc.*, 721 F.2d 1540, 220 USPQ 303 (Fed. Cir. 1983), cert. denied, 469 U.S. 851 (1984).

With regards to Applicant's other argument, it is respectfully submitted that the Examiner

has applied new citation s and passages from the Holloway et al., Pendleton Jr. et al., Hogden and Seare et al. reference to the amended features of the amended clams at the present time. As such, Applicant's remarks with regard to the application of Holloway et al., Pendleton Jr. et al., Hogden and/or Seare et al. to the amended claims are addressed in the above Office Action.

Conclusion

THIS ACTION IS MADE FINAL. Applicant is reminded of the extension of time policy as set forth in 37 CFR 1.136(a).

A shortened statutory period for reply to this final action is set to expire THREE MONTHS from the mailing date of this action. In the event a first reply is filed within TWO MONTHS of the mailing date of this final action and the advisory action is not mailed until after the end of the THREE-MONTH shortened statutory period, then the shortened statutory period will expire on the date the advisory action is mailed, and any extension fee pursuant to 37 CFR 1.136(a) will be calculated from the mailing date of the advisory action. In no event, however, will the statutory period for reply expire later than SIX MONTHS from the mailing date of this final action.

Any inquiry concerning this communication or earlier communications from the examiner should be directed to Robert W. Morgan whose telephone number is (571) 272-6773. The examiner can normally be reached on 8:30 a.m. - 5:00 p.m. Mon - Fri.

If attempts to reach the examiner by telephone are unsuccessful, the examiner's supervisor, Joseph Thomas can be reached on (571) 272-6776. The fax phone number for the organization where this application or proceeding is assigned is 571-273-8300.

Information regarding the status of an application may be obtained from the Patent Application Information Retrieval (PAIR) system. Status information for published applications may be obtained from either Private PAIR or Public PAIR. Status information for unpublished applications is available through Private PAIR only. For more information about the PAIR system, see http://pair-direct.uspto.gov. Should you have questions on access to the Private PAIR system, contact the Electronic Business Center (EBC) at 866-217-9197 (toll-free).

Robert Morgan

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